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Adaptive Infinite Impulse Response System Identification Using Elitist Teaching-Learning-Based Optimization Algorithm

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Abstract: Infinite Impulse Response (IIR) systems identification is complicated by traditional learning approaches. When reduced-order adaptive models are utilised for such identification, the performance suffers dramatically. The IIR system is identified as an optimization issue in this study. For system identification challenges, a novel population-based technique known as Elitist teacher learner-based optimization (ETLBO) is used to calculate the best coefficients of unknown infinite impulse response (IIR) systems. The MSE function is minimised and the optimal coefficients of an unknown IIR system are found in the system identification problem. The MSE is the difference between an adaptive IIR system's outputs and an unknown IIR system's outputs. For the unknown system coefficients of the same order and decreased order cases, exhaustive simulations have been performed. In terms of mean square error, convergence speed, and coefficient estimation, the results of actual and reduced-order identification for the standard system using the novel method outperform state-of-the-art techniques. For approximating the same-order and reduced-order IIR systems, four benchmark functions are examined utilizing GA, PSO, CSO, and BA. To demonstrate the improvements, the approach is evaluated on three conventional IIR systems of 2nd, 3rd, and 4th order models. On the basis of computing the mean square error (MSE) and fitness function, the suggested ETLBO approach for system identification is proven to be the best among others. Furthermore, it is confirmed that the suggested ETLBO method outperforms some of the other known system identification strategies. Finally, the efficiency of the dynamic nature of the control parameters of DE, TLBO, and BA in finding near parameter values of unknown systems is demonstrated through comparison data. The simulation results show that the suggested system identification approach outperforms the current methods for system identification.

Keywords: Infinite Impulse Response Filter, System Identification, Fitness Function, Unknown Coefficient Identification, Elitist Teacher learner-based Optimization, Mean Square Error.

I. INTRODUCTION

In Digital Signal Processing (DSP) applications, digital filters are crucial for signal separation and restoration. Signal processing, communication, military, and biological applications all employ these filters. The general classification for such digital filters is linear and nonlinear filters [1]. Adaptive filtering has recently received a lot of interest because of its many applications in signal processing, control systems, image processing, biomedical engineering, and communication systems. The two forms of adaptive filters are Infinite Impulse Response (IIR) and Finite Impulse Response (FIR) filters [2]. The output of an IIR filter is dependent on previous input and output samples, whereas the output of an FIR filter is only dependent on current and previous input samples [3]. Many academics prefer the IIR filter over the FIR filter because it needs a less number of system parameters for the same set of criteria [4]. Finite Impulse Response (FIR) systems and Infinite Impulse Response (IIR) systems are the two types of digital systems. The FIR system's output is only determined by the input signal (present and past inputs), but the IIR system's output is determined not only by the input (present and past) but also by the previous outputs. The IIR system has two flaws [5]. Foremost, the denominator coefficients were chosen incorrectly, which makes it unstable. This issue is solved by choosing the right search space. Second, it is not possible to obtain a perfectly linear phase response from it. Apart from these flaws, it is computationally efficient [6] because it requires fewer system coefficients than the FIR system. As a result, the adaptive IIR system has shown to be a superior solution to the system identification challenge. There are two procedures involved in implementing an adaptive IIR system identification. The first step is to select an appropriate identifying plant. Furthermore, an effective optimization approach is used to calculate the best filter coefficients [7]. The error minimization problem is used to express the system identification problem.

System identification is a challenging study area due to its non-linear and recursive model structure. Digital filters in digital processors are used to exclude a specified frequency band [8]. In the disciplines of control, signal processing, and communication, IIR filters are frequently employed instead of FIR filters for superior filtering. With a limited number of coefficients, the IIR filter's feedback produces an infinite impulse response [9]. The output filter in an FIR filter is only dependent on the current and prior inputs, as opposed to the output filter in an IIR filter, which is additionally dependent on past outputs. An IIR system of identification is one in which the coefficients of an adaptive filter are adaptively adjusted to suit the input/output configuration of an unknown system using an optimization method [10]. Traditionally, to minimise the error fitness function, gradient-based search algorithms such as the Quasi-Newton approach, Least Mean Square (LMS), and its derivatives were used. The nonlinear and multimodal error fitness function is used in the majority of adaptive IIR filter applications [11]. Using gradient-based search strategies to minimise such an error fitness function is difficult. Gradient-based search algorithms are unable to unite global minima and instead become trapped in local minima. Furthermore, because the poles of systems higher-order are located outside of the unit circle, they are linked to stability issues [12].

Unlike other inhabitant-based algorithms, the TLBO's performance is determined only by algorithm parameters such as population size, length of design variables, and iteration count [13]. The performance of evolutionary (EA) and swarm intelligence algorithms are influenced by both general and algorithm-specific characteristics. Tuning and regulating algorithm-specific parameters is difficult, time-consuming, and has a negative impact on the algorithm's exploitation capabilities [14]. The algorithm's performance is determined by the right selection of particular parameters. Excessive computational strain or local optimal convergence comes from poor selection. TLBO is simple, quick, straightforward to build, and powerful when compared to population-based algorithms [15]. As a result, utilising the ETLBO method, the study developed an optimization technique for IIR system identification. The remainder of the paper is laid out as follows. The literature review is outlined in Section 2. Section 3 discusses the digital filter design formulation, whereas Section 4 summarises the proposed methodology of the IIR system identification process. The suggested method's performance is examined in Section 5. Section 6 concludes with some recommendations for the future.

II. LITERATURE SURVEY

The authors reviewed several pieces of literature to build the suggested idea and highlight the need for improvement in the present model. Some of the existing research optimization techniques are included in this section, along with a brief description of their contribution.

Burhanettin Durmus *et al* [16] proposed an average differential evolution with a local search (ADE-LS) metaheuristic method for determining the best coefficients of an unknown Infinite Impulse Response (IIR) system as a system identifier. The presented approach reduces the difference between the adaptive IIR filter output and the unknown system output. The ADE-LS based adaptive IIR filter modelling with local search is used to achieve rapid convergence in the system identification issue. In this method, filter design with multimodal error surface, more exact prediction of filter coefficients is guaranteed. To demonstrate its performance, the ADE-LS algorithm is applied to four benchmarked IIR systems that have been well studied in the literature.

The Infinite Impulse Response (IIR) system is identified by Pasila Eswari *et al* [17] based on the error reduction idea. Because the parameter selection of a traditional PSO has an impact on the searching process, dynamic control parameters have been added to the mechanism to prevent premature solutions. Even if the starting control parameters are the worst, this change aids in achieving global optimum values. To demonstrate the improvements, the approach is tested on two conventional IIR systems of third and fourth-order models. Finally, the efficiency of the dynamic nature of the PSO control parameters in finding near parameter values of unknown systems is demonstrated by comparing data. To overcome the IIR system identification problem, Qifang Luo *et al* [18] suggested a modified whale optimization algorithm (WOA) with a ranking-based mutation operator, dubbed the RWOA. The RWOA incorporates a ranking-based mutation operator into the standard WOA to improve performance by accelerating convergence and then improving exploitation capabilities. In most cases, the experimental results of actual and reduced-order identification for a standard system using our proposed RWOA outperformed five state-of-the-art algorithms (including the basic WOA) in terms of improving the quality and stability of the results and significantly speeding up convergence.

Ruxin Zhao *et al* [19] designed and utilized a selfish herd optimization method based on chaotic strategy (CSHO) to solve the IIR system identification problem. Add a chaotic search strategy to CSHO, which is a more effective local optimization technique. Its purpose is to locate better candidate solutions surrounding the global optimum solution, which improves the algorithm's local search precision and uncovers prospective global ideal solutions. To test the efficiency of CSHO, we solve the IIR system identification challenge. For the trials, ten typical IIR filter models with the same order and decreased order were chosen. In tackling most IIR system identification issues, the experimental findings reveal that CSHO has improved optimization accuracy, convergence speed, and stability. Simultaneously, improved optimization parameters are obtained, and the disparity between actual and predicted output in test samples is reduced.

Farid Hammou *et al* [20] proposed the IIR system identification using an upgraded form of particle swarm optimization (PSO) termed Cooperation-Hierarchization PSO (CHPSO). In place of the standard rule for updating the best personal position of particles in the conventional PSO, the suggested approach introduces a novel strategy based on cooperation and hierarchization principles for updating the best personal positions of particles. This improvement not only adds particle variety but also provides a quick convergence to the best solution. CHPSO is more suited for IIR system identification because of these characteristics. Simulations are used to identify both full and reduced-order benchmarked IIR plants.

The optimal coefficients of an unknown infinite impulse response (IIR) system are estimated by Sandeep Singh *et al* [21] for the system identification issue using a new population-based technique called teacher learner-based optimization (TLBO). The TLBO algorithm is inspired by the classroom teaching-learning process and is devoid of algorithmic particular factors. In TLBO, each learner's difference means is determined, which is the difference between the classes and the teacher's existing mean results. This difference means is adjusted after each iteration and is in charge of keeping the algorithm diverse. The Mean Square Error (MSE) function is minimised and the optimal coefficients of an unknown IIR system are found in the system identification problem. The MSE is the difference between an adaptive IIR system's outputs and the outputs of an unknown IIR system. The unknown system coefficients of the same order and lower order cases have been found through exhaustive simulations.

Ali Mohammadi *et al* [22] reported AIO methodologies to simulate Infinite Impulse Response (IIR) systems for the design and optimization of IIR digital filters. The proposed methods include population-based particle swarm optimization, gravitational search algorithm, and inclined planes system optimization, as well as algorithms based on evolution strategy (genetic algorithm) and heuristic algorithms (particle swarm optimization, population-based; gravitational search algorithm, and inclined planes system optimization, both population-based and Newton's laws). In this study, the IIR system modelling is assessed for two distinct benchmark IIR plants with high and low orders as a restricted single-objective optimization problem in the Mean Squared Error (MSE) fitness function. Furthermore, the impact of lowering population size (search agents) on algorithm performance and efficiency is investigated. The simulation results demonstrate the research's success in terms of MSE, DoR, and IoS.

Using the Kautz basis expansion and the separable least squares approach, C.M. Cheng *et al* [23] devised a new Hammerstein system identification method. To limit the number of parameters to be identified, the linear subsystem's impulse response function (IRF) is enlarged by orthogonal Kautz functions, the pole parameters of which should be optimised. In addition, the linear and nonlinear parameters are estimated using the separable least squares optimization approach to enhance the condition number of the matrix during the identification process. In the least-squares framework, the separable least squares technique can estimate both linear and nonlinear parameters concurrently. This study presents an optimization approach for pole and nonlinear parameters based on the backpropagation through-time technique and the Levenberg-Marquardt algorithm.

MeeraDash *et al* [24] presented that the gradient search techniques that work well for FIR filters are not suited for IIR systems meanwhile they are prone to be caught in local minima. With this in mind, present population-based derivative-free diffusion particle swarm optimization (DPSO) techniques for estimating IIR system parameters. The algorithms are simulated and the steady-state and transient performances of benchmark IIR systems are investigated. In comparison to traditional least mean squared methods, the simulation results show that the suggested diffusion algorithms give an excellent improvement by resulting in faster convergence and a lower steady-state value. In the framework of system identification, Amjad J. Humaidi *et al* [25] presented an adaptation method for adaptive filtering of FIR and IIR digital filters. The traditional LMS method is combined with the GA (Genetic Algorithm) to create LMS-GA, a novel integrated learning algorithm. When only approximated data are available, the major goal of the proposed learning tool is to avoid local minima, which is a typical difficulty in traditional LMS algorithms and their modifications, and to approach the global minimum by computing the optimum values of the weights vector. The suggested LMS-GA is evaluated under various input signal situations, such as input signals having coloured features.

III. DESIGN FORMULATION OF DIGITAL FILTER

In a digital system, the computerised channel of a digital filter is a sophisticated framework for channelling various temporal signals. The insight the digital filtering is accomplished by firing a programme on a dedicated device, such as a Field Programmable Gate Array (FPGA), or by utilising a software application. Adjust the programme that describes the circuit to change the quality of a digital filter.

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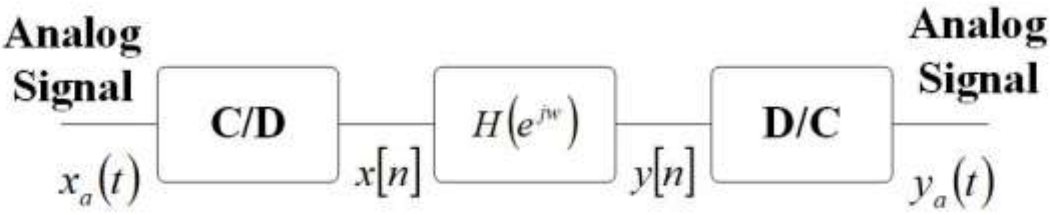

Figure 1: Analogous Signal Via Time Discrete Signal

Figure 1 depicts a typical setup for processing analogue signals using a time-discrete filter. Let $x_a(t)$ represent the analogue signal input and $y_a(t)$ represent the analogue signal output. Given an input signal to C/D, x[n] is the output signal, which changes to $\mathrm{x_a(t)}$, y[n] is the output signal, which changes to $\mathrm{y_a(t)}$, $H(e^{jw})$ is the filter's function of transfer, C/D is unbroken to the digital signal converter, and D/C is digital to the continuous signal converter. The impulse responses of an IIR filter do not always reach zero beyond a certain point, but instead, persist indefinitely. The impulse response time of an FIR filter, on the other hand, is restricted since it only stays at Null/Zero for a short time.

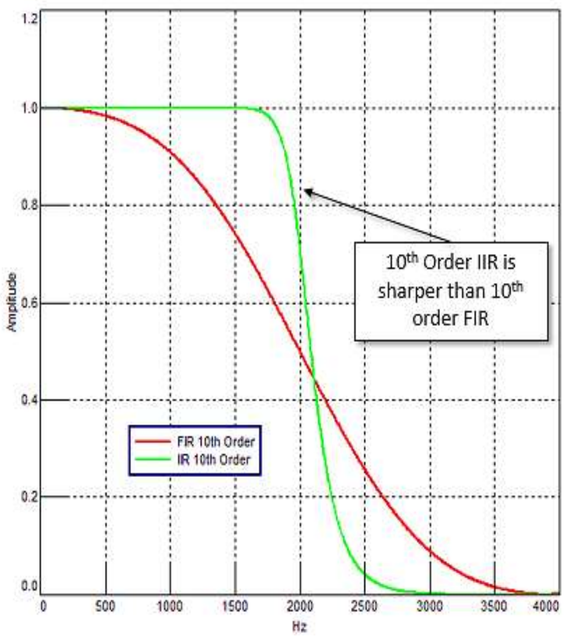

Figure 2: IIR Vs FIR Filter Comparison with Same Order

As illustrated in Figure 2, the sharpness of FIR and IIR filters for the same order differs dramatically. An IIR filter produces a sharper roll-off with the same order filter due to its recursive structure (Equation 1), where some of the filter output is utilised as input. Using an IIR filter, however, may have significant disadvantages. Each frequency has a different time delay. IIR filters are powerful DSP filters that are commonly available as "biquad" filters. Filters are useful in tasks where the line level is unimportant but the memory is limited. IIR is classified as follows:

$$x(n) = \sum_{k=0}^{\infty} h(k)u(n-k) \quad (1)$$

Calculating IIR Output with the given formula is unworkable. As a result, it may be rewritten using the linear constant-coefficient difference formula to get the finite number of poles p and zeros q.

$$x(n) = \sum_{k=0}^{q} b(k)u(n-k) - \sum_{k=1}^{p} a(k)x(n-k) \quad (2)$$

Filter elements and numerator polynomial coefficients a(k) and b(k) are roots equal to filter and zero, respectively. As a result, the Z-transform delay property may be used to explain the link between equation difference and Z-transform (transfer function).

$$\sum_{k=0}^{q} b(k)u(n-k) - \sum_{k=1}^{p} a(k)x(n-k) \overset{z}{\leftrightarrow} \frac{\sum_{k=0}^{q} b(k)z^{-k}}{1+\sum_{k=1}^{p} a(k)z^{-k}} \quad (3)$$

A. Problem Formulation of Infinite Impulse Response (IIR) System Identification

The main goal of this study's system identification is to iteratively change the parameters of the identifying IIR filter using an evolutionary algorithm until the filter's output signal matches that of the unknown system when the same input signal is applied to both the identifying IIR filter and the unknown system under consideration. In other words, the optimization process in system identification iteratively seeks the identifying IIR filter coefficients such that the filter's input/output relationship closely matches that of the unknown system.

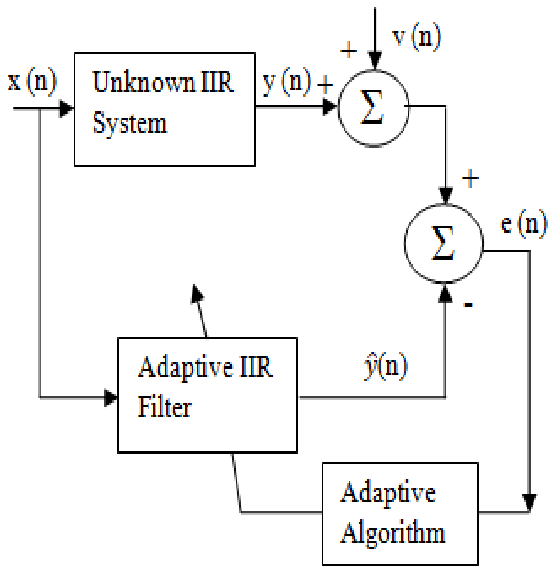

Figure 3: Block Diagram of an Adaptive IIR Filter for System Identification

The parameters are identified by an optimization method, and the schematic representation of system identification is supplied in a block diagram in accordance with the definition. The unknown plant of the transfer function $H_A(z)$is identified using the identifying IIR filter in such a manner that the outputs from both systems match closely for the same provided input in this design technique. The design approach of an IIR filter is discussed in this section. The following equation may be used to describe the input(x) and output(y) relationship:

$$y(i) + \sum_{k=1}^{n} a_k y(i-k) = \sum_{k=0}^{m} b_k x(i-k) \quad (4)$$

The order of the filter is the larger of n or m, where $x(i)$ and $y(i)$ are the filter's input and output. $H(Z)$ denotes the unknown plant's transfer function, and it's written as,

$$H(Z) = \frac{A(Z)}{B(Z)} \quad (5)$$

The polynomials $A(Z)$ and *B(Z)* of the IIR plant's Z-domain feed-forward and feed-back coefficient polynomials are $A(Z) = 1 + \sum_{k=1}^{n} a_k Z^{-k}$ and $B(Z) = \sum_{k=0}^{m} b_k Z^{-k}$. The unknown plant's z-domain transfer function is provided by

$$H(Z) = \frac{B(Z)}{A(Z)} = \frac{\sum_{k=0}^{m} b_k Z^{-k}}{1+\sum_{k=1}^{n} a_k Z^{-k}} \quad (6)$$

The coefficients of the unknown filter are a_k and b_k in the following equation. In the Z-domain, B(Z) represents a feed-forward (numerator) polynomial, whereas $A(Z)$ represents a feedback (denominator) polynomial. $y(n) = H(Z)\,x(n)$ indicates the output response of an unknown IIR filter. In the block diagram, the output of an unknown plant is provided by

$$y_0(n) = y(n) + v(n) \quad (7)$$

Where $v(n)$ is white Gaussian additive noise. When y(n) is substituted for value in equation (7), the resulting equation is

$$y(n) = \frac{A(Z)}{B(Z)} . x(n) + v(n) \quad (8)$$

The difference equation governs the adaptive filter,

$$\hat{y}(n) = H_A(Z)x(n) \quad (9)$$

The transfer function of the IIR Model is $H_A(Z)$. The adaptive filter's z-domain transfer function is provided by

$$H_A(Z) = \frac{\hat{B}(Z)}{\hat{A}(Z)} = \frac{\sum_{k=0}^{m} \widehat{b_k} Z^{-k}}{1+\sum_{k=1}^{n} \widehat{a_k} Z^{-k}} \quad (10)$$

Where, $\hat{A}(Z) = 1 + \sum_{k=1}^{n} \widehat{a_k} Z^{-k}$, and$\hat{B}(Z) = \sum_{k=0}^{m} \widehat{b_k} Z^{-k}$.$\hat{A}(Z)$ and $\hat{B}(Z)$ are feed-forward and feedback coefficient polynomials of the adaptive filter respectively and are given as

$$e(n) = y_0(n) - \hat{y}(n) \quad (11)$$

From equation (11), $e(n)$ reflects the error function between the output response of unknown filter $y(n)$ and adaptive filter $\hat{y}(n)$. The objective function in the system identification issue is the mean square error (MSE) of time samples, often known as the error fitness function and given as (12).

$$E[e(n)] = \frac{1}{N} \sum_{p=1}^{N} e(n)^2 \quad (12)$$

The total number of input samples is denoted by the letter N. The statistical expectation operator is denoted by $E[e(n)]$. The main goal of the proposed optimization algorithm considered in this work is to minimise the value of the error fitness MSE by iteratively adjusting the coefficient vector x of the adaptive filter's transfer function (9) consequently that the filter's output responses and the unknown plant's output responses match closely, and thus the error is minimised. An IIR filter might be unstable due to its design, preventing it from being calculated or applied to data.

IV. PROPOSED RESEARCH METHODOLOGY

The reducing error objective function between the output of the adaptive filter and the output of the unknown system for the same input is used to identify infinite impulse response (IIR) systems. With regard to the filter parameters, the error surface (objective function) in IIR filtering is typically non-quadratic and multimodal. Furthermore, the systems' poles are outside the unit circle, and higher-order systems are connected with stability concerns. Several practitioners use metaheuristic methods to circumvent these disadvantages. Population-based search strategies are determined as metaheuristic algorithms these are inspired by nature which employs random search and selection principles to give a globally optimum solution with rapid convergence. Many complicated and unresolved restricted optimization issues are addressed using such strategies. As a result, the study suggested the Elitist Teaching-Learning-Based Optimization Algorithm (ETLBO) to get an ideal set of coefficients such that when both systems are subjected to the identical input signal, the output of the adaptive IIR system perfectly matches the output of the unknown system.

Figure 3: Architecture of Research Work

Two procedures are involved in the execution of an adaptive IIR system identification. The first step is to select an appropriate identifying plant. Furthermore, an effective optimization approach is used to calculate the ideal filter coefficients. The problem of system identification is defined as an error minimization problem. In the elite teaching optimization algorithm, the elite strategy is introduced into the TLBO. The teacher-learner optimization algorithm is based on the classroom teaching-learning process. It is a basic, dynamic population-based method with no algorithm-specific parameters, allowing it to be used in a wide range of disciplines. The algorithm's exact parameters are represented by the mutation and crossover probabilities in the inertial weights, the acceleration rate in PSO, the scaling factor in Differential Evolution (DE), and the Genetic Algorithm (GA). On the other hand, other algorithms need the careful selection of algorithm-specific parameters that have a significant impact on the response. The optimal solution for each generation is retained. In addition, the inferior individuals will be replaced by elite ones during the iteration. Before the start of each iteration, the mutation mechanism will be randomly carried out on the elite individuals. Further, the repetitive ones will be deleted. In this way, those superior individuals can be retained in the later stage of the iteration, and the diversity of the population can be guaranteed effectively.

A. Elitist Teaching-Learning-Based Optimization Algorithm (ETLBO)

During iteration, the idea of elitism refers to the modification of the best solution by replacing the worst option. Because the TLBO algorithm considers the learners' mean value, there's a chance that duplicate values will appear once the elite solution is replaced with the worst. The solutions are modified in both phases (phase I and II) and the duplicate solutions are modified randomly throughout each generation of the TLBO algorithm. As a result, for the Elitist TLBO, we took into account twice the population size and the number of people, as well as the number of function evaluations necessary at the duplicate value removal stage, i.e. [29X9 no. of generations, Number of function evaluations necessary to eliminate duplicate values] where X denotes the population size. It's important to mention that the TLBO algorithm updates the solution both in the teacher and learner phases. If duplicate solutions are found during the duplicate elimination stage, they are randomly adjusted. As a result, the total number of function evaluations in the TLBO method is equal to (2 ×population sizes × generations) + (function evaluations necessary for duplication removal). The aforementioned formula is utilised throughout this article's experimental work to count the number of function evaluations while doing tests using the TLBO method. Meanwhile, the function evaluations needed for duplication removal are unknown, tests with various population sizes and based on these experiments are done. Figure 4 depicts the suggested ETLBO algorithm's flow chart.

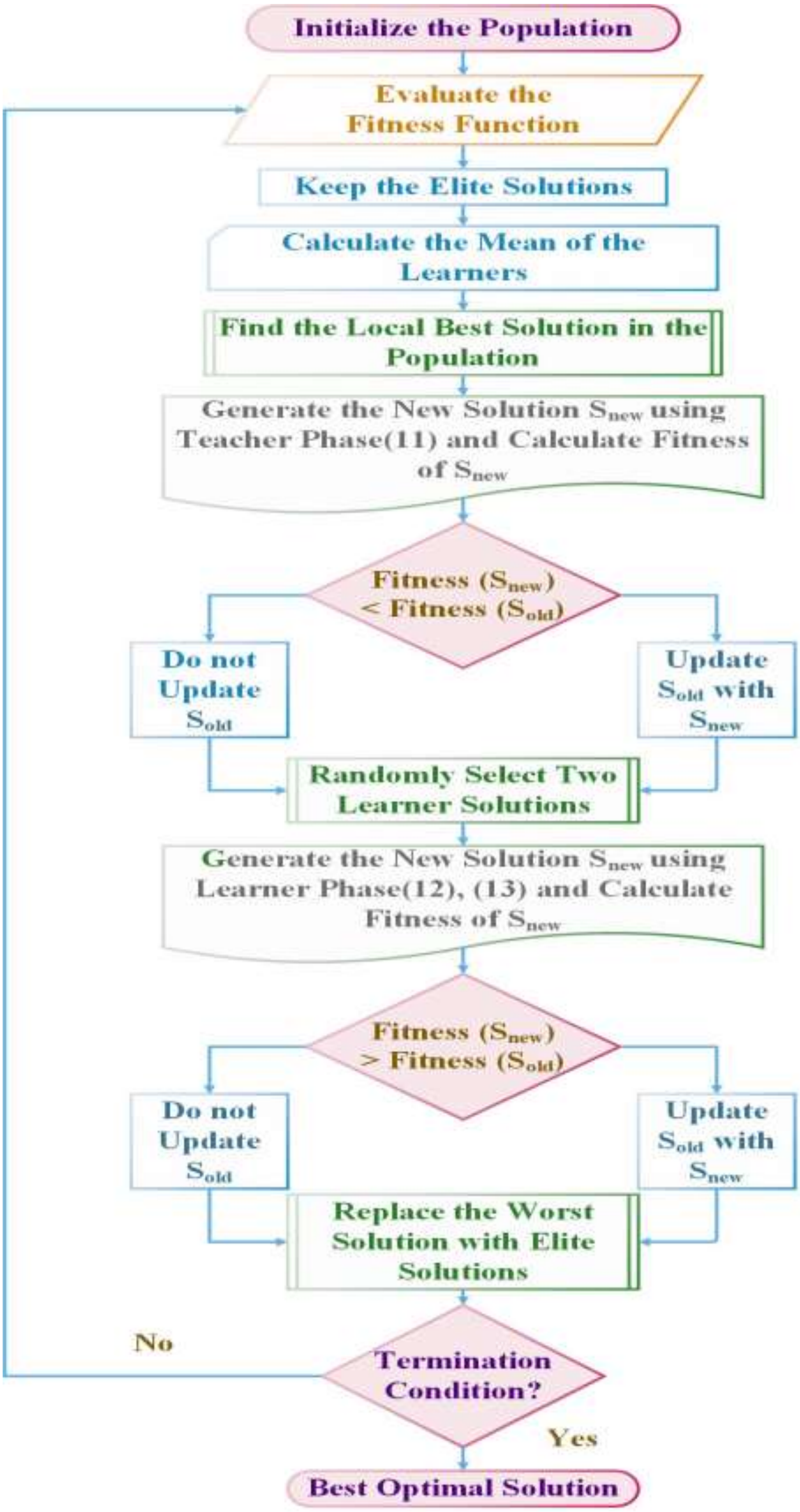

Figure 4: Flowchart of the Proposed ETLBO Optimization Algorithm

The population (individuals) is regarded as a class of learners in this technique, and distinct attributes associated with each individual are compared to different subjects. The fitness value of the learners is regarded as the best value of iteration, and the instructor is considered the greatest value of iteration. The Teacher phase and the Learner phase are the two phases of TLBO. All learners are updated depending on the instructor in the Teacher phase; however, all learners are updated based on the other student in the Learner phase. Before moving on to the next iteration, the instructor is updated after the two phases have been finished. TLBO, like other stochastic-based approaches, works its way to the best solution iteratively.

A.1.1 Teacher Phase in TLBO

In the teacher phase, learners acquire knowledge from the teacher. The finest solution among the population is taken as a teacher solution. The overall learning average of the outcomes is improved in class in the teacher stage. The best solution among the learner solutions is measured as the teacher solution. The distinction among the active mean of the learners in all topics and teacher solutions is given by,

$$Difference_{mean} = rand^{*}\left(S_{best} - T_f S_{mean}\right) \quad (13)$$

Where, S_{mean} represents the mean of the learner result in all the subjects. T_f states the factor of teaching, it will be 1 or 2 based on rounding up criteria and $rand$ is a value between [0, 1].

$$T_f = round\left[1 + \left(rand(0,1)^{*}(2-1)\right)\right] \quad (14)$$

The active solution is restructured in the teacher phase as,

$$S_{new} = S_{old} + Difference_{mean} \quad (15)$$

The updated S_{new} is accepted only if the fitness of S_{new} is better than S_{old}. In the learner phase, the accepted solution from the teacher phase becomes the input. The teacher phase can guide the population to approach the optimum solution and accelerate the convergence speed.

A.1.2 Learner Phase in TLBO

The learning phase simulates the behaviour of the student through the interaction or discussion of his or her knowledge with other students or friends in the class. He/she may acquire some knowledge on a concerned subject from his/her friends by the method of discussion or interaction. A student can also acquire some new knowledge from his friends if his friends have more expertise than him on the concerned subject. Randomly select two learners S_a and S_b.

Table 1: Pseudocode of Learner Phase

IF $\boldsymbol{S_a}$ has more knowledge than $\boldsymbol{S_b}$,
$\boldsymbol{S_{new} = S_{old} + r_2(S_a - S_b)}$
ELSE
$\boldsymbol{S_{new} = S_{old} + r_2(S_b - S_a)}$
END

Table 1 shows the Pseudocode of Learner Phase. The S represents the revised solution in the learner's stage, while the r_2 represents a random value among [0, 1]. Only if S_{new} fitness is better than S_{old}, is the updated S_{new} accepted in the learner phase, and the process continues until the termination requirement is reached. The idea of elitism is added in TLBO to promote convergence to an optimal solution. To begin with, the most effective options are saved as elite solutions. The current iteration's poorest solutions are replaced with the prior iteration's finest ones.

Algorithm: Elitist Teaching-Learning-Based Optimization Algorithm (ETLBO)

For i=1: iteration
T_F = round (1+rand (0.1) (2-1))

$$X_i(new) = X_i(old) + rand(1)(X_{teacher} - T_F + X_{means})$$

end for
By using the learner phase population and renewing the population by comparing the fitness of the old population and new population and the best solution is stored in the learner phase.
For i = 1: iteration (no. of iteration in the population-based)
If (fitness of $\mathbf{X_i(old)}$< fitness of $\mathbf{X_i(new)}$)

$$\mathbf{X_i} = \mathbf{X_i(new)}$$

else

$$\mathbf{X_i} = \mathbf{X_i(old)}$$

end if
end for
Check for termination criteria until it reaches the best optimal solution and else go to step 6.
Repeat this phase until the best optimal solution is stored.
Optimal Solution

Following the conclusion of the Teacher and Learner phases, the algorithm is modified to update the teacher value before the next iteration begins. The same pseudo-code may be used to solve the maximising issue. The main difference in maximising is that when two learners are considered, a learner's value is updated depending on the learner who provides the fitness value higher. A random input signal is taken based on the order of the filter. By using known parameters, we are evaluating the fitness function by using the input signal and storing the output signal. Now, initialize the random population and filter the input signal by using known parameters and unknown parameters and find out the MSE between the known and unknown parameters. Then, using the teacher phase and learner phase reduces the MSE Value and fitness function. By using the teacher phase create a fresh population and by modifying the solution in the first population based on the finest solution.

V. EXPERIMENTATION AND RESULT DISCUSSION

Unknown plants are modelled for system identification using a filter with the same order as the plant or a reduced-order filter. ETLBO's real and reduced-order convergence characteristics are included in the findings. ETLBO is used to identify the IIR System in this project. The system set up in table 2 is used to simulate the results in MATLAB 2020a. Operation System for this software is Windows 10 Home and its memory capacity is 6GB DDR3. Intel Core i5 @ 3.5GHz is the Matlab processor. The simulated results are used to determine the algorithms' performance in recognising the system.

Table 2: Simulation System Configuration

MATLAB	Version R2020a
Operation System	Windows 10 Home
Memory Capacity	6GB DDR3
Processor	Intel Core i5 @ 3.5GHz
Simulation Time	10.190 seconds

The simulation research is conducted in MATLAB to illustrate the ETLBO algorithm's capability for identifying IIR plants. A white signal with a zero mean, unit variance, and uniform distribution is used as the input. The additive noise is a 103-variance Gaussian white signal. The results of the DE, TLBO, BA, PSO, and MFO techniques are also acquired through simulation to compare the performance of the new approach. All three algorithms start with a population of 50 people. DE was run using the following simulation parameters: number of bits per dimension 10, mutation probability (0.1), and single-point crossover probability (0.9). PSO's simulation parameters are as follows: inertia weight is reduced linearly from 0.9 to 0.4, both acceleration constants are set to 2, and random integers are selected from the range [-1 1]. To identify four benchmark IIR systems, various tests are conducted. The order of the filter and its coefficients determine the length of the design variable. Using a scaling factor of 0.5 and a crossover rate of 0.9, the ETLBO works on just common parameters particular to DE.

A model for an unknown plant can be created in one of two ways: (i) using a filter with the same order as the plant, or (ii) using a reduced-order filter. The capacity of an algorithm to represent a plant using a reduced-order model determines its overall performance. A reduced-order model is utilised to evaluate the performance of GA, PSO, and CSO for each standard test function. This section contains the results achieved in terms of convergence characteristics and MSE for both actual and reduced-order IIR plants. For the actual order of the IIR plants, the estimated and real parameters, the MSD, and the calculation time are also reported.

A. Simulation Results of the IIR Identification System

Comprehensive assessments, including Pole-Zero plots, are used to analyse the accuracy modelling process and confirm that the generated IIR filtering systems match their comparable benchmark IIR plant transfer function. A white noise string with a length of K = 250 is used as the input signal. The method meets the optimality, stability, and other desirable characteristics for any number of independent runs, according to experimental data.

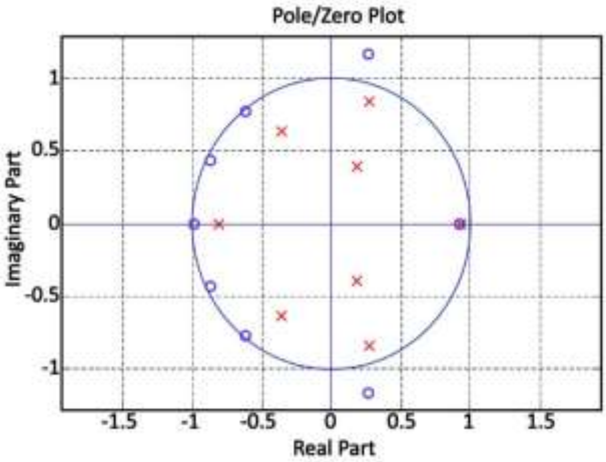

Figure 5: Pole-Zero Plots of the Best System Modelled for all IIR Systems

The pole-zero plots of the principal plants in the IIR proposed system are shown in Figure 5. ETLBO is shown to have the best fitness without any sudden oscillations. The unit circle plot for the design problem illustrated that all poles lie inside the unit circle which validates the stability of the system. The stability of the filter does not influence by the location of zeros.

B. Performance Metrics of Proposed System

The performance metrics MSE and convergence profile are used to measure the performance of the same-order and reduced-order system identification problems. To calculate the percentage improvement of ETLBO over DE, performance metrics such as TLBO, BA, PSO, and MFO are used for same-order system identification, but MSE is the only performance measure used for reduced-order system identification. In this situation, the stability restriction acts as a damping factor, and the second component of the cost function becomes zero as soon as the proposed filter's stability criterion is met. The method then searches for the best coefficient estimation (optimum) to solve the multimodal error surface issue in the preferred order space. It is feasible to examine all optimum and stable solutions for each predicted order in each iteration.

$$Fitness = (\propto\times MSE) + \left((1-\propto)\times\left(\frac{O}{Q-1}.\frac{\Omega}{\Omega T}\right)\right) \quad (16)$$

Where ∝ is the effect factor of optimum and minimum filter order modelling, and (1-∝) is the effect factor of adaptive IIR system coefficients optimal design. The parameter O is the best and smallest estimated integer for the filtering system order, Q-1 indicates the highest modelable order (Q is the main/unknown plant's filter order), Ω denotes the number of filter poles outside and on the unit circle's border, and ΩT indicates the total number of filter poles. It should have a value of zero, and the optimization process should continue until the constraint is encountered. The identifying procedure is intelligently done as the fitness function is derived.

B.2.1 Second-Order IIR System Identification

The transfer function of the second-order system used to approximate the same order system is given by

$$H_s(z) = \frac{b_0+b_1z^{-1}}{1-a_1z^{-1}-a_2z^{-2}} \quad (17)$$

$$H_Z(Z) = \frac{1.25Z^{-1}-0.25Z^{-2}}{1-0.3Z^{-1}+0.4Z^{-2}} \quad (18)$$

The numerator and denominator coefficients a0, a1 and b1, b2, respectively, are optimised to decrease the difficulty of system identification. Table 3 shows the coefficients found, which lead to the best approximation of the unknown system using evolutionary algorithms.

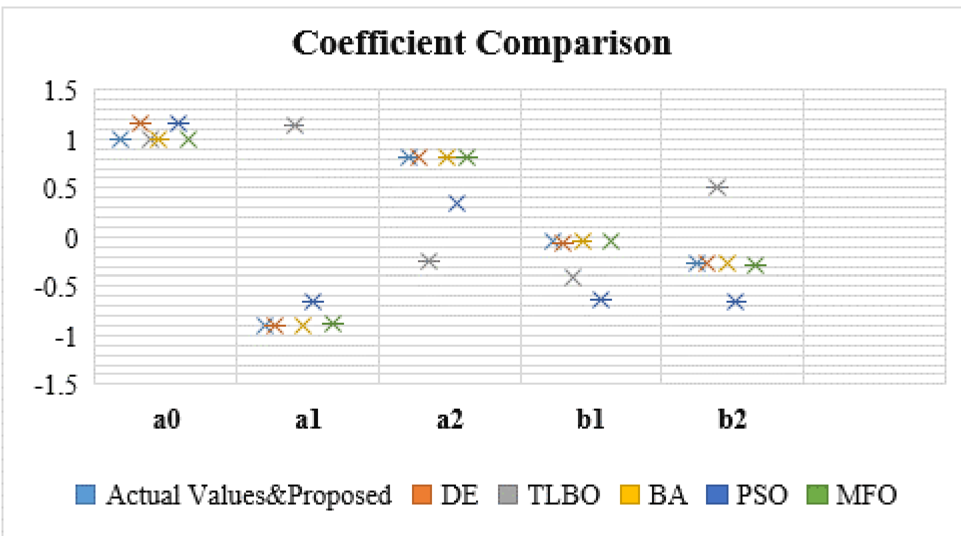

Figure 6: Coefficient Comparison for Second-Order Optimized Using DE

Figure 6 illustrates the coefficient comparison for second-order IIR system unknown plant identification optimized using DE. The estimated coefficient values for the same order system are graphically represented, the data range is from -0.4 to 1.2. Further, the values are listed in Table 3 with the MSE values.

Table 3: Optimized Coefficients and MSE Obtained Using ETLBO for 2nd Order IIR System

Runs	a1	a2	b1	b2	MSE
Run1	1.2500	-0.2500	-0.3000	0.4000	3.1342e-26
Run2	1.2500	-0.2500	-0.3000	0.4000	9.3872e-28
Run3	1.2500	-0.2500	-0.3000	0.4000	5.8780e-30
Run4	1.2500	-0.2500	-0.3000	0.4000	6.3736e-26
Run5	1.2500	-0.2500	-0.3000	0.4000	2.0303e-25

Case 2: Reduced Order

The transfer function of a second-order system used to approximate the third-order system is given by

$$H_r(z) = \frac{b_0 + b_1 z^{-1}}{1 - a_1 z^{-1} - a_2 z^{-2}} \quad (19)$$

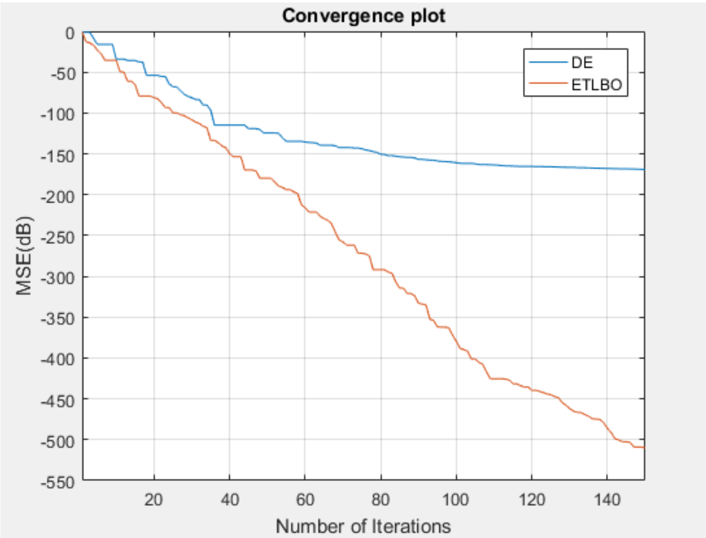

Figure 7: Convergence Plot of Example Modelled Using 2nd Order IIR Filter

Figure 7 shows the convergence plot for the reduced-order approximation, with ETLBO achieving a minimum error of roughly 48 dB at the 140th iteration. Furthermore, based on the steepness, it can be deduced that ETLBO's convergence speed is substantially faster than DE's.

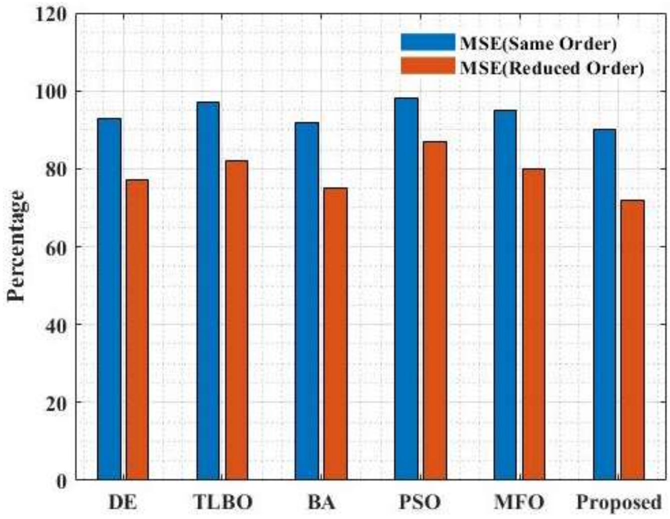

Figure 8: Percentage Improvement in MSE Value of Second-Order IIR

The percentage improvement in the performance of ETLBO over DE, TLBO, BA, PSO, and MFO is graphically presented in Figure 8. The observed MSE for the same-order system is 93.43%, 97.82%, 92.67%, 98.37%, and 95.73% for ETLBO compared to DE, TLBO, BA, PSO, and MFO. Further, MSE for the reduced-order system is 77.61 %, 82.41 %, 75.86 %, 87.39%, and 80.12% for ETLBO compared to DE, TLBO, BA, PSO, and MFO, respectively.

C. Third Order IIR System Identification

A third-order unknown system with the transfer function defined by is used to approximate the third-order system.

$$Hs(z) = \frac{a_0+a_1z^{-1}+a_2z^{-2}}{1-b_1z^{-1}-b_2z^{-2}-b_3z^{-3}} \quad (20)$$

In this scenario, four methods are used to optimise the system parameters a0, a1, a2, b1, b2, and b3. Table 3 contains the estimated coefficients.

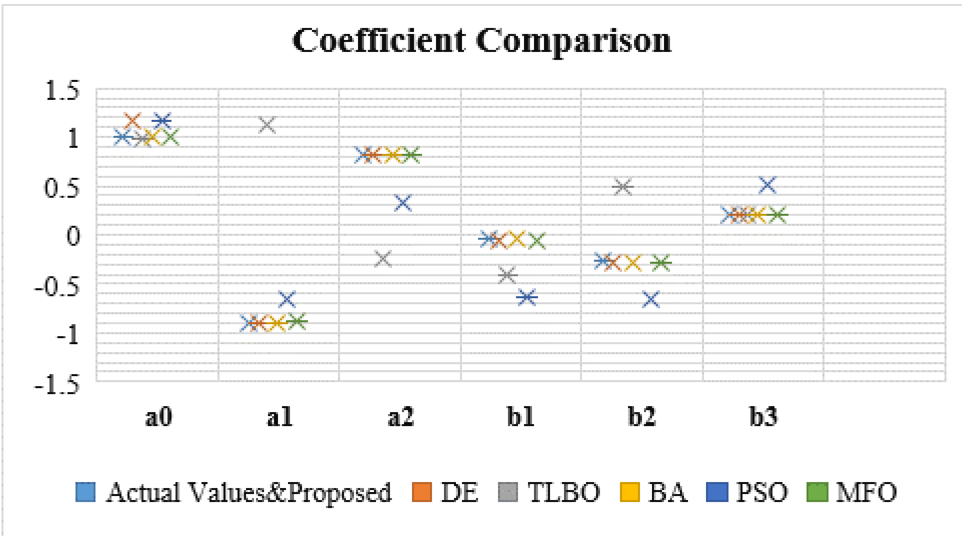

Figure 9: Coefficient Comparison for Third Order Optimized Using DE, TLBO, BA, PSO and MFO

Figure 9 shows that, when compared to other techniques, the coefficient values calculated with ETLBO approximate the real parameter values. This depicts the comparison of the coefficient for DE, TLBO, BA, PSO and MFO with the actual values. In the unknown coefficient value of third-order analysis obtained ETLBO value is the same as that of actual values.

Case 2: Reduced Order

Here, the system identification is based on modelling the third-order system using a second-order unknown system whose transfer function is given by

$$Hr(z) = \frac{a_0+a_1z^{-1}}{1-b_1z^{-1}-b_2z^{-2}} \quad (21)$$

Five benchmark functions (G03, G06, G10, G18, and G19) are studied to determine the influence of population size, the number of generations, and elite size on the TLBO algorithm's convergence rate. The benchmark function under consideration contains several types of objective functions (polynomial, cubical, linear, quadratic, and non-linear), as well as varied numbers of variables. With 240000 function evaluations, the TLBO algorithm is applied to the functions under consideration. The fitness value (i.e., function value) and function evaluations are shown on a graph. The function value used is the average of the function values from ten separate independent runs. The convergence graphs for several benchmark problems are shown in Figs 3-7. The convergence rate of the method for function G03 rises with the increase in population size, as seen in Fig. 3. As the population grows from 75 to 100, the convergence rate is nearly the same. In addition, when the elite size grows from zero, the algorithm's convergence rate decreases.

The fitness value (i.e. function value) and function evaluations are shown on the graph. The function value that was used as the average of 10 distinct independent runs. The convergence graphs for several benchmark problems are shown in Figure 10. The algorithm's rate of convergence rises as the population size grows. As the population grows from 75 to 100, the convergence rate is nearly the same. Furthermore, when the elite size grows from zero, the algorithm's convergence rate decreases.

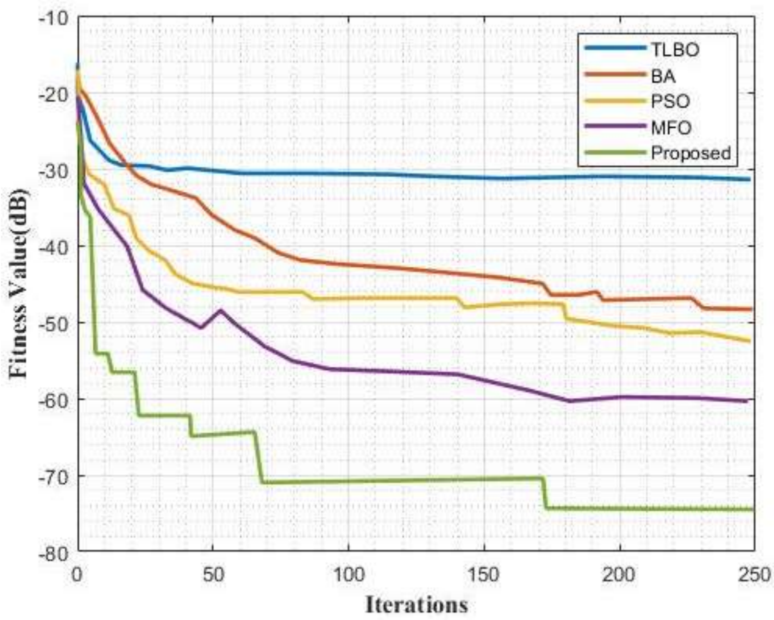

Figure 10: Convergence Behaviours for Third Order MSE Fitness Values

Figure 10 shows the convergence profile for MSE values. ETLBO requires 155 iterations to converge to the minimal fitness value of roughly 36 dB, as seen in the graph above. Furthermore, it can be deduced from the steepness that ETLBO's convergence speed is substantially faster than that of TLBO, BA, PSO, and MFO.

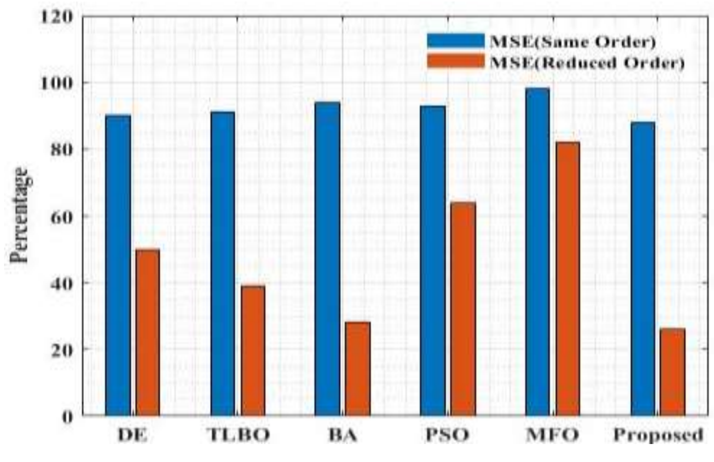

Figure 11: Percentage Improvement in MSE of Third Order IIR System

Figure 11 demonstrates the improvement in the performance of TLBO over previously published techniques for system identification utilising decreased order. For the same-order system, the percentage improvement in MSE for ETLBO compared to DE, TLBO, BA, PSO, and MFO is 92.64 percent, 99.58 percent, and 98.62 percent, 96.14 percent, and 94.39 percent, respectively. The percentage improvement noticed in MSE for the reduced-order system is 67.54 %, 58.61 %, 85.88 %, 90.75%, and 53.82% for ETLBO compared to DE, TLBO, BA, PSO and MFO, respectively.

D. Fourth Order IIR System Identification

In this case, the fourth-order system is approximated using the same order unknown IIR system whose transfer function is given by

$$H_S(z) = \frac{b_0+b_1z^{-1}+b_2z^{-2}+b_3z^{-3}}{1-a_1z^{-1}-a_2z^{-2}-a_3z^{-3}-a_4z^{-4}} \quad (22)$$

The numerator and denominator coefficients a0, a1, a2, a3 and b1, b2, b3 and b4 are optimised to solve the system identification issue. Table 3 shows the coefficients found, which lead to the best approximation of the unknown system using evolutionary procedures.

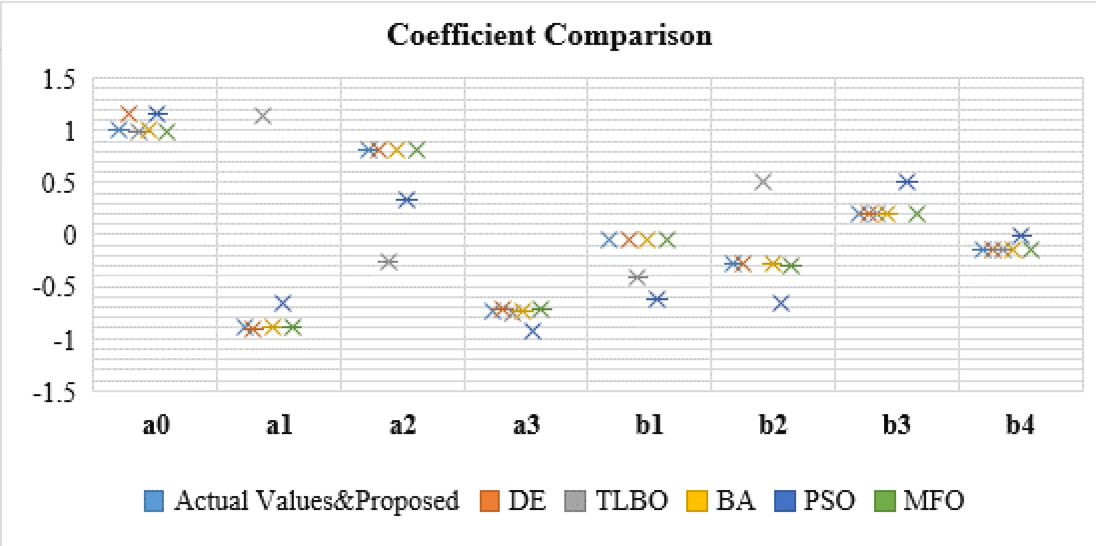

Figure 12: Coefficient Comparison for Fourth Order Optimized Using DE, TLBO, BA, PSO and MFO

Figure 12 illustrates the coefficient comparison for fourth-order IIR system unknown plant identification optimized using DE, TLBO, BA, PSO and MFO. The estimated coefficient values for the same order system are graphically represented, the data range is from -1.0 to 1.5. In the unknown coefficient value of third-order analysis obtained ETLBO value is the same as that of actual values.

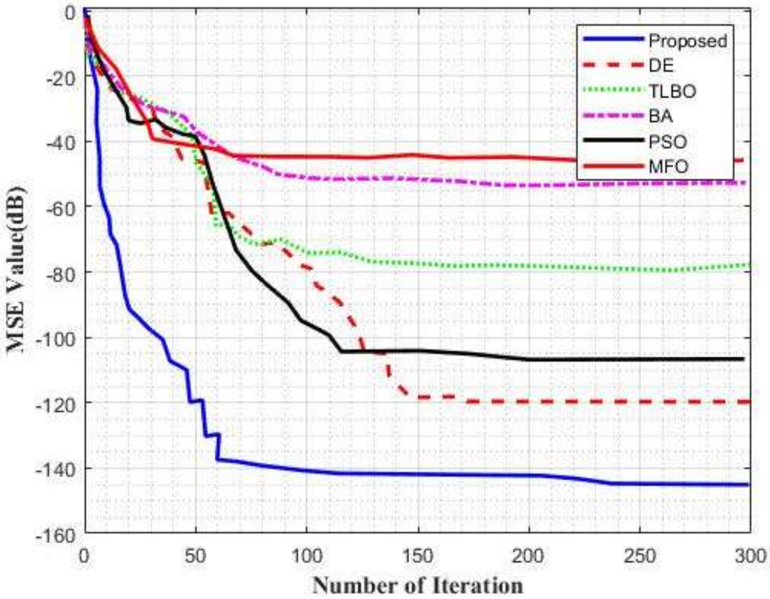

Figure 13: Convergence Behaviours for Fourth Order MSE Fitness Values

The convergence profiles are shown in Figure 13. In 52 rounds, ETLBO converges to a fitness value of roughly -10 dB. TLBO contributes to a fitness value of -23 dB in 100 iterations, but DE requires 149 iterations to obtain a fitness value of -25 dB. Consequently, after 55 cycles, MFO converges to an MSE of -10 dB. Based on these observations one can conclude that the convergence rate of ETLBO is faster than other applied algorithms.

Case 2: Reduced Order
The transfer function of the reduced fourth-order system is given by

$$H_r(z) = \frac{b_0+b_1z^{-1}+b_2z^{-2}+b_3z^{-3}+b_4z^{-4}}{1-a_1z^{-1}-a_2z^{-2}-a_3z^{-3}-a_4z^{-4}} \quad (23)$$

These observations indicated the suggested algorithm's capacity to provide acceptable results in terms of system characteristics, MSE value, and elapsed time. Furthermore, TLBO is devoid of algorithmic specific parameters, which regulate the algorithm's variety. The algorithm's exploitation and exploration phases are also ensured by the Teacher-phase and Learner-phase.

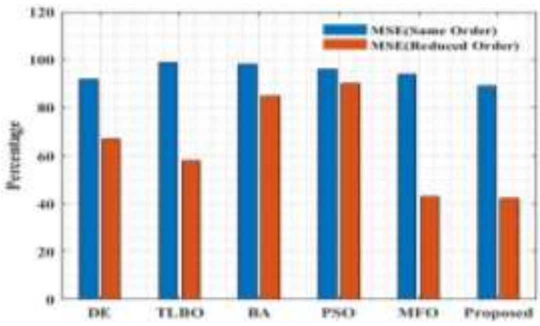

Figure 14: Percentage Improvement in MSE Value of Fourth Order IIR System

For the same order and reduced-order systems, the TLBO algorithm is compared to the other methods in terms of percentage improvement. Figure 14 illustrates this proportion graphically. For the same order, the ETLBO method provides a 98 percent improvement over all other algorithms employed. The percentage improvement of TLBO over DE, TLBO, BA, PSO, and MFO for a reduced-order system is 50.23 percent, 39.12 percent, 28.45 percent, 64.36 percent, and 82.19 percent, respectively.

E. Comparison Analysis of Proposed Technique
The dominance of the adaptive IIR system identification using ETLBO over existing techniques for system identification problems using DE, TLBO, BA, PSO, and MFO for both same-order and reduced-order unknown systems is demonstrated. Table 4 summarises the MSE results.

Table 4: Comparison of Different Reported Algorithms Using Same-Order and Reduced-Order System

Reference	Year	Algorithm	MSE	
			Same Order	Reduced Order
Pedro Lagos-Eulogio [26]	2017	DE	NR∗	6.8500×10^{-02} (-11.6431 dB)
Singh [8]	2019	TLBO	3.1287×10^{-12} (-115.0464 dB)	1.8004×10^{-04} (-37.4463 dB)
Manjeet Kumar [27]	2016	BA	5.8182×10^{-6} (−52.3521 dB)	4.3986×10^{-5} (−43.5669 dB)

With a reduced-order system, Pedro Lagos-Eulogio et al [26] used the DE technique to create an adaptive IIR filter whose response matches the second-order unknown system and reported a mean square error of 6.8500 1002×10^{-02} (-11.6431 dB). Singh *et al* [8] presented the design of an adaptive IIR filter using TLBO, and a mean square error of 3.1287 × 10−12 (-115.0464 dB) with the same order and 1.8004×10^{-04} (-37.4463 dB) is achieved with a reduced-order system. The design of a second-order adaptive IIR filter utilising BA and MSE of 5.8182 $\times10^{-6}$ (52.3521 dB) has been preserved using the same order as Manjeet Kumar et al [27]. Further reduced-order 4.3986×10^{-5} (-43.5669 dB) of MSE is attained.

VI. RESEARCH CONCLUSION

For many years, adaptive IIR filtering has been a hot topic of research, with applications in signal processing and communication. In this article, an Optimization Algorithm based on Teacher Learning is used to identify IIR systems. For system identification issues, the optimal coefficients of an unknown infinite impulse response (IIR) system are determined using a unique population-based method called Elitist teacher learner-based optimization (ETLBO). The objective of the system identification contest is to find the optimal coefficients for an unknown IIR system while minimising the Mean Square Error (MSE). The MSE is the difference between the outputs of an adaptive IIR system and the outputs of an unknown IIR system. With the help of 2nd, 3rd, and 4th order IIR system identification, exhaustive simulations were performed to determine the unknown system coefficients of the same order and reduced order cases. The utilisation of ETLBO optimization improves the accuracy of obtaining the best set of coefficients significantly.

The simulation of the results is done in MATLAB. ETLBO is used to optimise a few benchmark transfer functions. The results show that in second-order systems, ETLBO offered the least MSE. The ETLBO method performed well in matching the adaptive filter coefficients with the unknown system. When compared to DE, TLBO, BA, PSO, and MFO, it completed system identification in fewer iterations. ETLBO finds the best, most optimum solution. The proposed approach shows convergence in a fewer number of iterations than the other algorithms. Generally, ETLBO is successful in finding the minimum MSE solution among the reported methods and can obtain higher-quality estimated coefficients with better convergence properties. This research can also be used for the detection of complicated fractional systems. Furthermore, the proposed technique should be investigated in the future for the Volterra-based nonlinear system identification problem.

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